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Improving Tracking through Human-robot Sensory Augmentation

Yanan Li*, *Member, IEEE*, Jonathan Eden*, *Member, IEEE*, Gerolamo Carboni*, and Etienne Burdet, *Member, IEEE*

Abstract—This paper introduces a *sensory augmentation* technique enabling a contact robot to understand its human user’s control in real-time and integrate their reference trajectory information into its own sensory feedback to improve its tracking performance. The human’s control is formulated as a feedback controller with unknown control gains and desired trajectory. An unscented Kalman filter is used to estimate first the control gains and then the desired trajectory. The estimated human’s desired trajectory is used as augmented sensory information about the system and combined with the robot’s measurement to estimate a reference trajectory. Simulations and an implementation on a robotic interface demonstrate that the reactive control can robustly identify the human user’s control, and that the sensory augmentation improves the robot’s tracking performance.

I. INTRODUCTION

How to program a robot working in contact with its human user? While the benefits of contact robots are suggested by the effects observed during physical tasks carried out between humans exchanging haptic information [1], [2], [3], contact robots have so far made little use of the opportunities of interactive control [4]. It is often stated that collaborative strategies between the robot and human should be designed to use the best of their respective capabilities. By this it is usually meant that the robot would carry heavy loads according to reference trajectories identified by the human user, who has the superior analysis and sensorimotor intelligence capabilities [5], [6]. While the aforementioned works focus on how humans and robots can share the task load and control effort [7], [8], [9], [10], we propose here a different strategy according to which *a robot and its human partner could use haptic information during physical interaction to complement their own sensing*. This *sensory augmentation* is in line with the notion of the observation-control duality in control theory [11] but has not been studied for human-robot collaboration.

External sensors such as (3D) camera, ultrasonic sensors and LIDAR have been used to infer the partner’s movement intention, based on which reactive/collaborative control could be designed e.g. for obstacle avoidance in multi-agent systems [12]. Could the haptic information exchanged during physical

interaction be used to infer the movement intention of the human user and improve the performance of the robot? Many research works in assistive devices estimate/recognize the human user’s movement intention or command [13], e.g. assistance of path following by rollators and wheelchairs [14], [15]. These works typically use the user’s information to modulate the robot’s controller, but do not use that information to improve the robot’s sensing and knowledge of the task.

In [2], it has been shown that when humans in physical contact (e.g. through an object) carry out a common action, they improve their sensorimotor performance by understanding their partner’s control and extracting their motion goal. It has been further shown in [3] that these benefits, which apply to both partners regardless of their relative ability, are due to *haptic communication* mediated through mechanical interaction between the partners. Using this communication, the partners are able to understand each other’s motion goal and integrate this information to improve their performance beyond their individual tracking capability. In this paper, we develop an algorithm to replicate this neural mechanism which can be used to improve the sensorimotor performance of a human-robot system. This algorithm is fundamentally different from the aforementioned approaches for multi-agent systems and assistive devices, by integrating the partner’s sensing to one’s own and thus improves the task performance.

To infer the desired trajectory of a partner, it is necessary to know their control law. However, the robot cannot a-priori know the control used by the human, so they must learn it during the interaction. This requires the design of an observer through which both partners will understand each other’s control in order to predict their motion planning. This paper first develops such an observer-predictor pair. The interactive behaviour and potential benefits of the resulting robotic partner are then tested in three steps:

- Simulations examine whether in ideal cases the estimation techniques result in correct identification, and in similar improvements to that observed in human interactions.
- Experiments between a robot and a known secondary controller (or “virtual” human, VH) are implemented on a physical system to validate that the estimation is robust to real-world disturbances.
- An experiment with human subjects verifies that the improvements from the robot partner’s sensory augmentation are robust to unmodelled human factors.

*: The first three authors contributed equally to the work.

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II. PROBLEM FORMULATION

A. System dynamics

The dynamics of an object manipulated at a common end-effector point by a robot and a human can be described as

$$u + u_h + \nu = M\ddot{x} + C\dot{x} \quad (1)$$

where $u \equiv u(t)$ and $u_h \equiv u_h(t)$ are the robot and human control inputs, respectively, ν is white noise in the robot and human's control inputs, $x \equiv x(t)$ is the (common) end-effector position in task space, $M \equiv M(x)$ is the object's mass matrix, and $C\dot{x} \equiv C(x, \dot{x})\dot{x}$ is the Coriolis and centrifugal force term.

We assume that the robot and human generate motions with little error and effort [16], corresponding to minimising the respective cost functions

$$J \equiv \int_{t_0}^{\infty} (x - \tau)' Q_x (x - \tau) + \dot{x}' Q_{\dot{x}} \dot{x} + u' u \, dt, \quad (2)$$

$$J_h \equiv \int_{t_0}^{\infty} (x - \tau_h)' Q_{h,x} (x - \tau_h) + \dot{x}' Q_{h,\dot{x}} \dot{x} + u_h' u_h \, dt$$

where the subscript h stands for human, $'$ is the transpose operator, $x \equiv x(t)$, $\tau_h \equiv \tau_h(t)$, $\tau \equiv \tau(t)$ are functions of time, $Q_{h,x}$, $Q_{h,\dot{x}}$, Q_x , $Q_{\dot{x}}$ are subject specific positive semi-definite matrices, and t_0 is the start time of one trial. $Q_{h,x}$ and Q_x are used to express the minimisation of the human and robot's tracking errors, respectively, and $Q_{h,\dot{x}}$ and $Q_{\dot{x}}$ the minimisation of their velocity. The weights of the human and robot's control inputs u and u_h are assumed to be 1 for analysis convenience. τ_h and τ are the human and robot's desired trajectories which are unknown to the partner and modelled as constants that may evolve with the system noise.

To facilitate the analysis, the system dynamics eq.(1) and cost functions of the human and robot eq.(2) can be written in state-space form as

$$\begin{aligned} \dot{\xi} &= A\xi + B(u + u_h + \nu), \\ \xi &\equiv \begin{bmatrix} x - \tau \\ x - \tau_h \\ \dot{x} \end{bmatrix}, \quad A \equiv \begin{bmatrix} 0 & 0 & 1 \\ 0 & 0 & 1 \\ 0 & 0 & -M^{-1}C \end{bmatrix}, \quad B \equiv \begin{bmatrix} 0 \\ 0 \\ M^{-1} \end{bmatrix}, \\ J &= \int_{t_0}^{\infty} \xi'(t) Q \xi(t) + u'(t) u(t) \, d\tau, \\ J_h &= \int_{t_0}^{\infty} \xi'(t) Q_h \xi(t) + u_h'(t) u_h(t) \, d\tau \end{aligned} \quad (3)$$

where

$$Q \equiv \begin{bmatrix} Q_x & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & Q_{\dot{x}} \end{bmatrix}, \quad Q_h \equiv \begin{bmatrix} 0 & 0 & 0 \\ 0 & Q_{h,x} & 0 \\ 0 & 0 & Q_{h,\dot{x}} \end{bmatrix}.$$

In this formulation, both the robot and human use the same state information ξ to minimise their own cost function. Each of them generates motor commands minimising their respective cost function using the LQR algorithm [17]:

$$u = -L\xi, \quad L = B'P, \quad (4)$$

$$A'P + PA + Q - PBB'P = 0$$

$$u_h = -L_h\xi, \quad L_h = B_h'P_h, \quad (5)$$

$$A'P_h + P_h A + Q_h - P_h B B_h' P_h = 0$$

where L and L_h are the control gains of the human and robot, resulting from their individual cost matrix parameters, and P and P_h are computed by solving the respective Riccati equation. These control gains correspond to Cartesian stiffness and viscosity. They vary slowly and smoothly with posture due to the nonlinear kinematic transformation between the joint and Cartesian spaces [18], and are assumed to be constant for small movements.

B. Sensory augmentation

Suppose that the robot and human's sensing provides them with a measurement of the system's common position x and velocity \dot{x} as well as their own desired trajectory, i.e.

$$\begin{aligned} y &\equiv \begin{bmatrix} x - \tau \\ \dot{x} \end{bmatrix} + \varepsilon \equiv H\xi + \varepsilon, \quad H \equiv \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix}, \\ y_h &\equiv \begin{bmatrix} x - \tau_h \\ \dot{x} \end{bmatrix} + \varepsilon_h \equiv H_h\xi + \varepsilon_h, \quad H_h \equiv \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \end{aligned} \quad (6)$$

where ε_h , ε represent the respective white noises resulting from the different measurement capabilities of each partner.

How to estimate ξ based on y_h and y ? In the human-human collaborative tracking task of [2], the partner's desired trajectory inferred from haptic information was combined with their reference estimation obtained from visual sensing [3], which resulted in tracking improvement. Similarly, could an observer combining the user and partner's estimated reference be implemented according to their respective noise statistics? In this paper, we apply such a method for human-robot interaction and design the robot's control.

As in the human model of [3], we assume that the two agents estimate each other's desired trajectory and combine it with their own. In particular, the robot can use

$$y \equiv [(x - \tau)' (x - \hat{\tau}_h)' \dot{x}']' \quad (7)$$

to replace the measurement in eq.(7) where $\hat{\tau}_h$ is the estimate of τ_h . In this way, it is expected that the estimation of the reference trajectory will be improved due to the additional sensory signal. We elaborate into how this *sensory augmentation* strategy is realised in the following section.

III. ESTIMATION OF HUMAN'S CONTROL

In this section, we develop a method to estimate the human's control input u_h in eq.(5), which includes two parts unknown to the robot, namely the subject and task specific control gain L_h and their desired trajectory τ_h . As both of them have to be estimated, we extend the system state from the robot's point of view to

$$\bar{\xi} \equiv [(x - \tau)' (x - \tau_h)' \dot{x}' \bar{L}'_{h,x} \bar{L}'_{h,h} \bar{L}'_{h,\dot{x}}]' \quad (8)$$

where $\bar{\cdot}$ is the vectorisation operator. The last three components which are from the unknown human's control gain, i.e.

$$L_h \equiv [L_{h,x} \ L_{h,h} \ L_{h,\dot{x}}] \quad (9)$$

correspond to the three variables $x - \tau$, $x - \tau_h$ and \dot{x} , respectively. Then, eqs.(3,7) are extended to

$$\begin{aligned} \dot{\hat{\xi}} &= \bar{A}\bar{\xi} + \bar{B}(u + \nu), \\ y &= \bar{H}\bar{\xi} + \varepsilon, \quad \bar{H} \equiv \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \end{bmatrix} \\ \bar{A} &\equiv \begin{bmatrix} 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ a_{21} & a_{22} & a_{23} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}, \quad \bar{B} \equiv \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} \\ a_{21} &\equiv -M^{-1}L_{h,x}, \quad a_{22} \equiv -M^{-1}L_{h,h}, \\ a_{23} &\equiv -M^{-1}(C + L_{h,\dot{x}}). \end{aligned} \quad (10)$$

To estimate L_h and τ_h , noting the non-linearity resulting from the multiplication of the unknown controller gains with the state within the extended state, we develop an observer using an unscented Kalman filter (UKF, [19]) with the observer

$$\dot{\hat{\xi}} = \hat{A}\hat{\xi} + \bar{B}(u + \nu) + K(y - \hat{y}), \quad \hat{y} = \bar{H}\hat{\xi} \quad (11)$$

where \hat{A} is the estimate of \bar{A} with L_h replaced by \hat{L}_h , \hat{y} is the estimate of y and K is the UKF gain. Yielding the estimated extended state $\hat{\xi}$, the estimated human's control gain and desired trajectory are obtained.

Note that \bar{H} is a sparse matrix, which indicates that the measurable system information is limited. Therefore, it is difficult to simultaneously estimate the human's control gain and desired trajectory. To address this issue, in this paper we propose to estimate L_h and τ_h sequentially: the human's control gain L_h is estimated from an initial trajectory $\tau_h(t)$ known to the robot (which is shown for the human to track), after which any human's desired trajectory τ_h can be estimated. The following two subsections describe how L_h and τ_h can be estimated.

A. Estimation of human's control gain

Supposing that the human's initial desired trajectory is known to the robot, the robot's 'measurement' yields

$$\begin{aligned} \begin{bmatrix} x - \tau \\ x - \tau_h \\ \dot{x} \end{bmatrix} + \varepsilon_1 &= \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \end{bmatrix} \bar{\xi} + \varepsilon_1, \\ \bar{y}_1 &\equiv \bar{H}_1 \bar{\xi} + \varepsilon_1. \end{aligned} \quad (12)$$

Then, $\hat{\xi}$, the robot's estimate of $\bar{\xi}$, can be obtained from the observer (11) with the replacements $y \rightarrow \bar{y}_1$ and $\hat{y} \rightarrow \hat{y}_1 \equiv \bar{H}_1 \hat{\xi}$. The UKF gain is updated iteratively with each time step $k \Delta t$ as

$$K_1 = P_1 \bar{H}_1' R_1^{-1} \quad (13)$$

where P_1 is obtained by solving the Riccati equation

$$P_1 \bar{A}' + \bar{A} P_1 - P_1 \bar{H}_1' R_1^{-1} \bar{H}_1 P_1 + Q_k = 0. \quad (14)$$

Q_k and R_1 are covariance matrices of white noises ν and ε_1 , respectively, reflecting the relative skill of the agent in their prediction/measurement. This minimises the estimation error

$$J = E[\|\hat{\xi} - \bar{\xi}\|^2] \quad (15)$$

and the last three components of $\hat{\xi}$ form the estimate of ξ used to estimate the human control gain \hat{L}_h . In performing this estimation we note that the system eq.(10) with measurement eq.(12) is not completely observable. Therefore the estimation requires the injection of persistently exciting noise into the reference of one or both of the partners.

B. Estimation of the partner's desired trajectory

With \hat{L}_h the estimate of the human's control gain L_h , it becomes possible to estimate the system state ξ including the human's desired trajectory τ_h , provided that the robot and human's desired trajectories are persistently exciting. In particular, the robot's 'measurement' including \hat{L}_h becomes

$$\begin{aligned} \begin{bmatrix} x - \tau \\ \dot{x} \\ \hat{L}_{h,x} \\ \hat{L}_{h,h} \\ \hat{L}_{h,\dot{x}} \end{bmatrix} + \varepsilon_2 &= \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \bar{\xi} + \varepsilon_2, \\ \bar{y}_2 &\equiv \bar{H}_2 \bar{\xi} + \varepsilon_2. \end{aligned} \quad (16)$$

Similarly as in the previous subsection, $\hat{\xi}$, the robot's estimate of $\bar{\xi}$, can be obtained from the observer (11) with the replacements $y \rightarrow \bar{y}_2$ and $\hat{y} \rightarrow \hat{y}_2 \equiv \bar{H}_2 \hat{\xi}$. The UKF gain is updated iteratively with each time step $k \Delta t$ as

$$K_2 = P_2 \bar{H}_2' R_2^{-1} \quad (17)$$

where P_2 is obtained by solving the Riccati equation

$$P_2 \bar{A}' + \bar{A} P_2 - P_2 \bar{H}_2' R_2^{-1} \bar{H}_2 P_2 + Q_k = 0. \quad (18)$$

R_2 is covariance matrix of white noise ε_2 . Then, the second component of $\hat{\xi}$ can be used to obtain the estimate of the human's desired trajectory τ_h .

IV. SIMULATION

To demonstrate the benefits of the proposed sensory augmentation method, we simulate a scenario where a human arm is rigidly connected to a robot at a common end-effector while both track the same reference trajectory, i.e. $\tau_h(t) = \tau(t) \forall t$. This is simulated by considering the system dynamics eq.(1), with mass $M=6\text{kg}$ and 0 Coriolis and centrifugal component. Motor noise ν is added to the control input (generated using `randn()` in Matlab). The human and robot are assumed to have equal skill and use the cost functions of eq.(2) with $Q_x = Q_{h,x} = 20000 \text{ m}^{-2}$ and $Q_{\dot{x}} = Q_{h,\dot{x}} \text{ s}^2 \text{ m}^{-2}$.

First, we suppose that the human and robot know each other's initial desired trajectory. The robot's desired trajectory is a 1m square wave plus a sweeping signal $[\sin(t) + \sin(2t) + \sin(3t)]/10^4$ while the human's desired trajectory is a 0.1m square wave plus another sweeping signal $[\cos(t) + \cos(2t) + \cos(3t)]/10^4$. The covariance matrices of noises are $Q_k = 10^{-10} 1_8 \text{ m}^{-2}$ and $R_1 = 10^{-10} 1_4 \text{ m}^{-2}$, respectively. An UKF is implemented to deal with the non-linearity in the system eq.(10) and estimate the control gains \hat{L} and \hat{L}_h .

Second, the identified estimated control gains are used to estimate the partner's new desired trajectory. The noise covariance matrices are $Q_k = 10^{-10} 1_8 \text{ m}^{-2}$ and $R_2 = 10^{-10} 1_7 \text{ m}^{-2}$, respectively. An UKF is implemented again to obtain the estimated desired trajectories $\hat{\tau}$ and $\hat{\tau}_h$, respectively.

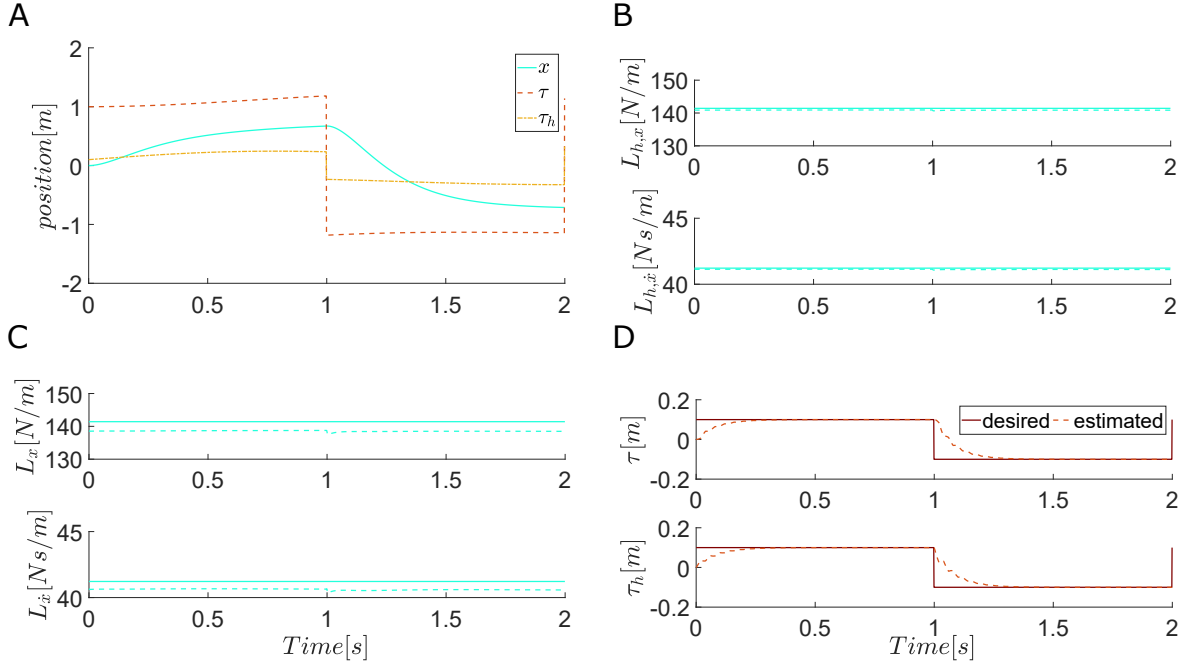


Fig. 1. Estimation of the partner's control in the final 2 seconds of the trajectory. A: The actual trajectory is in the middle between the human's and robot's desired trajectories, as they have the same weights in their respective cost functions. B: Human's control gains $L_{h,x}$, $L_{h,\dot{x}}$ (solid lines) and their estimates by the robot (dotted lines) almost overlap. C: Robot's control gains L_x , $L_{\dot{x}}$ (solid lines) and their estimates by the human partner (dotted lines) almost overlap. D: The human and robot are able to estimate each other's desired trajectory.

A. Estimation of the partner's control gain and trajectory

We first simulate estimation of the partner's control gain. Fig.1A illustrates the position profile during the reaching task: since the human and robot have the same weights in their respective cost functions, the actual trajectory is exactly in the middle between human's and robot's desired trajectories. Figs.1B and 1C show that the human's and the robot's control gains can be reliably estimated by the partner.

With the estimated partner's control gain, we are ready to simulate estimation of the partner's new desired trajectory. For this purpose, we assume that the human's and robot's desired trajectories become a square wave with magnitude of 0.1m. Note that they are unknown to their respective partner and that the same trajectories are considered as this will be used for goal integration in the next subsection. Fig.1D illustrates the estimation results of the partner's desired trajectory. In particular, the upper figure shows that human is able to estimate the robot's desired trajectory τ , with a certain error due to the continuous change of the movement direction. Correspondingly, the bottom figure shows similar performance of estimating the human's desired trajectory τ_h by the robot.

B. Goal integration

After the partners estimate each other's desired trajectory, they can combine it with their own motion planning. When the two agents track the same reference these two pieces of information can be used to improve the estimation of the 'true' reference trajectory. To do so the robot uses the 'measurement'

$$y \equiv [(x - \tau)', (x - \hat{\tau}_h)', \dot{x}']' + \varepsilon \quad (19)$$

and the human

$$y_h \equiv [(x - \hat{\tau})', (x - \tau_h)', \dot{x}']' + \varepsilon_h. \quad (20)$$

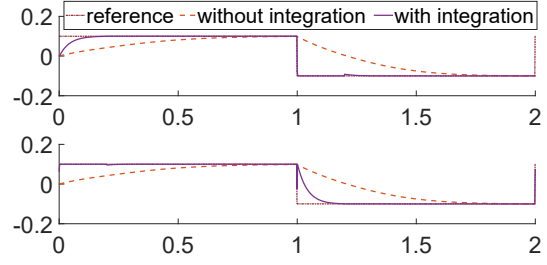
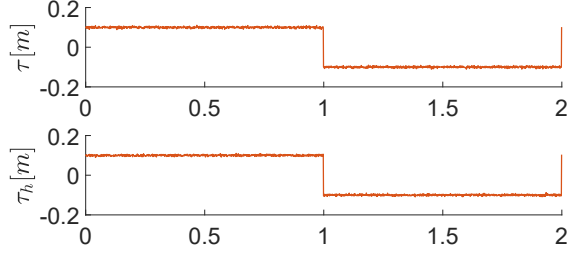
The same reference trajectory is set as a 0.1m square wave. Other parameters remain the same as in the previous subsection.

Fig.2 illustrates the simulation results with and without integrating the estimated partner's desired trajectory under three conditions reflecting different relative skill levels in interpreting partner information and measurement:

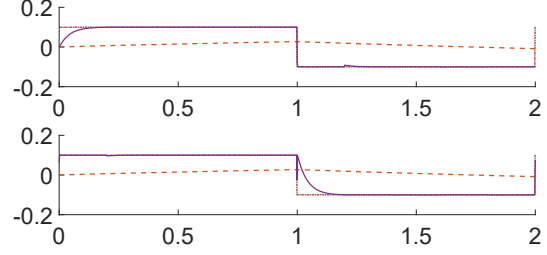
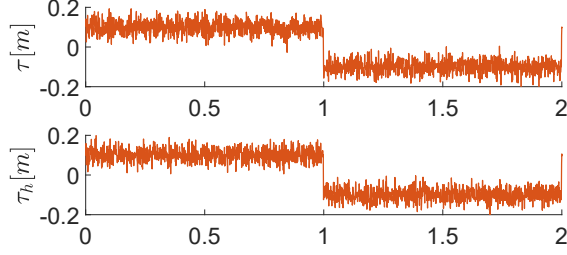
- Superior measuring: both partners have excellent measuring ability with the covariance matrix of the measurement noise set as 10^{-5} m^{-2} for both.
- Inferior measuring: the covariance matrix of the measurement noise is set as 10^{-3} m^{-2} for both.
- One superior partner and one inferior partner: the covariance matrix of the measurement noise is set as 10^{-5} m^{-2} for the human and 10^{-3} m^{-2} for the robot. All other parameters are held identical.

It is observed that the estimation is refined when the estimated partner's desired trajectory is integrated. Both partners improve their individual tracking, no matter if their partner is superior or inferior in using their vision to measure the reference trajectory. These results correspond to the observations of human-human interaction in [3]. How about the overall tracking performance? Fig.3 illustrates that when integrating the estimated partner's desired trajectory, the tracking performance is improved compared to that without integration. These results show that human-robot interaction can be used to improve not only the reference estimation, but also the reference tracking of collaborative robots.

A: Superior, Superior



B: Inferior, Inferior



C: Inferior, Superior

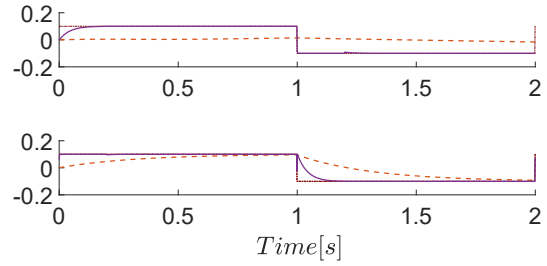
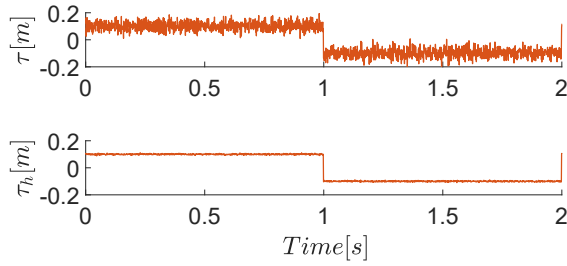


Fig. 2. Integration of the estimated partner's desired trajectory. The left panels illustrate the measurement of each partner in the presence of sensory noise, while the right panels show that the error in estimation of the reference is reduced for both partners superior in the tracking task (A), both inferior (B), and with one superior and one inferior (C).

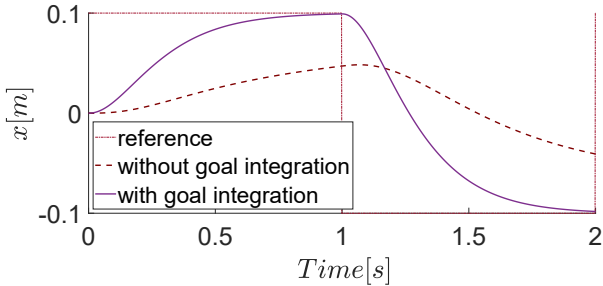


Fig. 3. Tracking performance with a superior simulated human and an inferior robot. The performance improvement resulting from integrating the estimated partner's desired trajectory is also found for the cases of the human and robot both superior and both inferior, but is omitted.

V. EXPERIMENTAL RESULTS

To validate the accuracy of the estimation and the capability of the algorithm for sensory augmentation when applied to a physical system, we implemented a similar scenario as in the simulation, where two agents are rigidly connected to a common 1 degree of freedom (DoF) robotic interface. One of the two agents is the robot, which is estimating its partner. This partner is either i) a human, or ii) a 'virtual' human

(VH) which is used during the validation of the algorithm's estimation capability. The VH implements the control law eq.(5) with control gains that the robotic agent has to identify. By using the VH we have a benchmark with known parameters on which the developed algorithms can be systematically tested.

The experiments are implemented on the Hi5 robotic interface [20]. Fig.4A depicts this robot which constitutes a 1 DoF revolute joint. After Coulomb and viscous friction compensation, the system can be modeled with the system dynamics eq.(1), where the inertia is given by $M=0.004 \text{ kg m}^2$ and there is 0 Coriolis and centrifugal contribution. The robot and VH actuate the interface through a directly driven DC motor, while the human partner can provide actuation through the robotic joint which they are rigidly attached to. The robot agent's component of the control uses the cost functions of eq.(2) with $Q_x = 1 \text{ rad}^{-2}$ and $Q_{\dot{x}} = 0 \text{ s}^2 \text{ rad}^{-2}$. In addition to the real-time haptic feedback provided through mechanical interaction throughout the experiment, position feedback for the human operator is shown on a monitor.

First, in Section V-A, using the VH partner we suppose that the partners know each other's desired trajectory and observe the robot's estimation of the control gain. The VH's desired

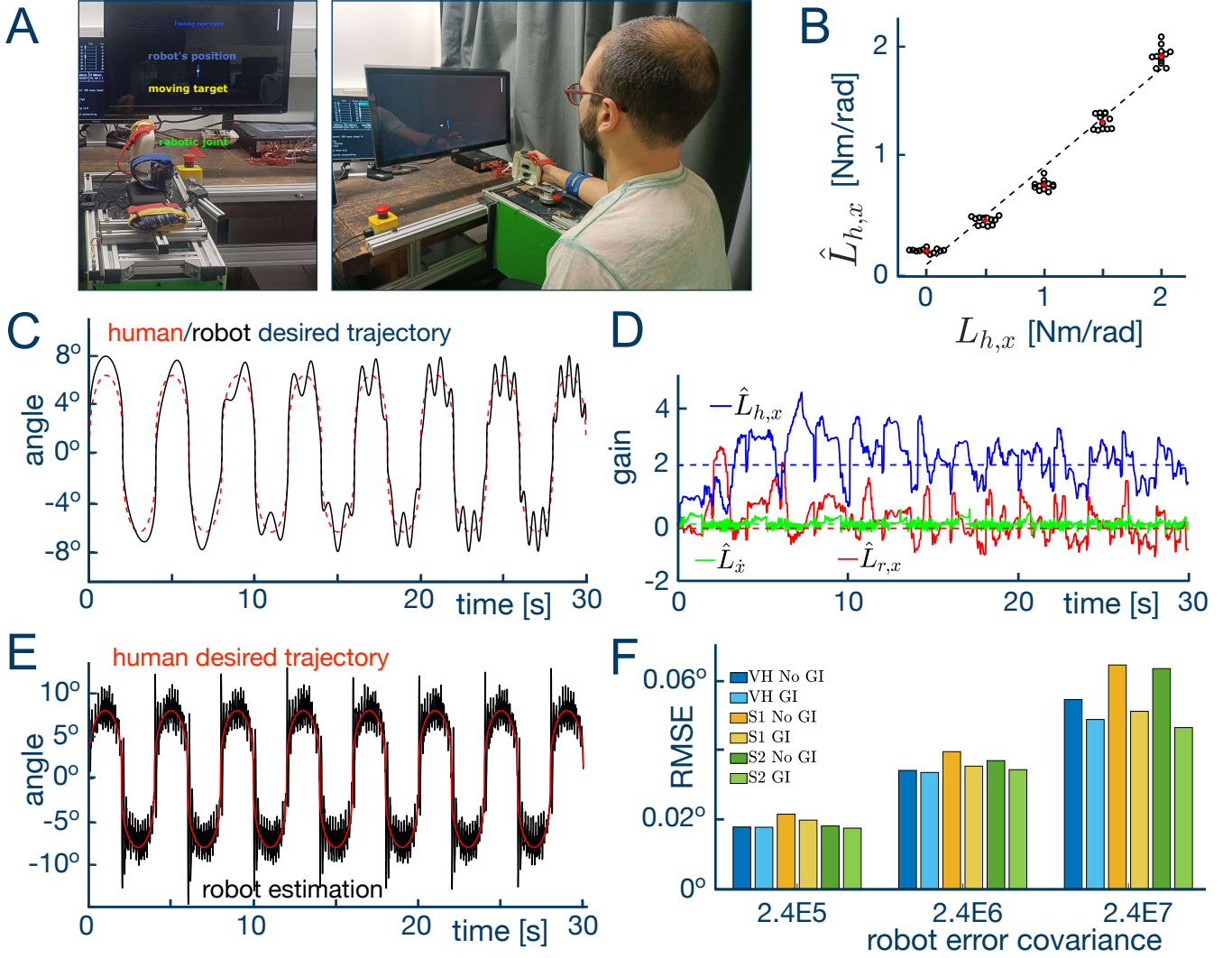


Fig. 4. Experimental validation. A: Hi5 revolute joint robotic interface and experimental scenario with a human subject. The interface is equipped with a DC motor that allows for the rendering of interaction torques in real-time due to physical coupling. The apparatus includes a monitor mounted in front of the manipulandum for providing visual feedback to the human user of the manipulandum's position and the moving reference. This interface is used throughout the implementation. B: Estimation of the VH's varying control gains for 12 trials. The mean estimated values across all trials at the same gain are shown with red crosses, while the individual estimations are represented as black circles. C: Robot's and VH's desired reference trajectories. The red dashed line constitutes the VH's desired trajectory τ_h given by eq.(21) and the black line τ represents the robot's desired trajectory which has an additional imposed chirp signal. D: The robot's VH gain estimates as a function of time for VH gain $L_h = [0, 2, 0]$. In each case, the mean value over the last 8 seconds is shown with the dashed line. E: Robot's estimation of the human trajectory. The black line denotes the estimation obtained for a representative trial when $L_h = [0, 2, 0]$, while the red line denotes the VH's desired trajectory. F: Root mean squared error (RMSE) of the robot error state estimation with and without goal integration for increasing values of robot error covariance expressed in rad^{-2} (VH: 'virtual' human; GI: goal integration; S1: human subject 1; S2: human subject 2). The goal integration improves the robot's estimation when interacting with the VH and two human subjects, under conditions of different measurement noise levels.

trajectory is set as a rounded square wave with magnitude of 8° and period of 4s given by

$$\tau_h(t) = 8(\sin(0.5\pi t))^{\frac{1}{3}}. \quad (21)$$

This trajectory is chosen as it approximates a point to point reaching task including both forward and backward movements. The robot's desired trajectory is the VH's desired trajectory plus a sweeping chirp signal with frequencies ranging from 0Hz to 2Hz to provide persistent excitation. The covariance matrices of noises are $Q_k = 10^{-2} \mathbf{1}_6 \text{ rad}^{-2}$ and $R_1 = 10^{-10} \mathbf{1}_3 \text{ rad}^{-2}$, respectively. An UKF [19] is implemented to deal with the non-linearity in the system eq.(10) and to obtain the estimated control gain \hat{L}_h , which is varied,

in different trials, over a range of values.

Second, in Section V-B, one of the estimated control gains from the first experiment is used to estimate the VH's now unknown desired trajectory. Covariance matrices of noises are set to $Q_k = 10^{-2} \mathbf{1}_6 \text{ rad}^{-2}$ and $R_2 = 10^{-10} \mathbf{1}_5 \text{ rad}^{-2}$, respectively. An UKF is implemented again to obtain the estimated desired trajectory $\hat{\tau}_h$. These two validating experiments confirm that the estimation can still work despite the unmodelled nonlinearities and quantisation present in the physical system.

Third in Section V-C, the estimated VH's desired trajectory is used, in a manner consistent with the findings of [3], as additional sensory information about the system. This information is combined with the robot's measurement, using

a third UKF, in order to improve the robot's estimate of an uncertain reference trajectory.

Finally in Section V-D, the same procedure is performed as a pilot study on two human subjects. The results are then compared to the VH partner performance and confirm that the algorithm is able to deal with the additional variance and unmodelled non-linearities, and that the effect of sensory augmentation is similar to that observed in previous human-human interaction studies [2], [3].

A. Estimation of the 'virtual' human's control gain

In this subsection, we estimate the VH's control gain for the known VH and robot trajectories (shown in Fig.4C). With fixed robot control, we vary the imposed VH partner gain from $L_h = [0, 0, 0] \text{ N m rad}^{-1}$ to $L_h = [0, 2, 0] \text{ N m rad}^{-1}$ in increments of $L_{h,h} = 0.5 \text{ N m rad}^{-1}$. Twelve trials are recorded at each gain level to verify the estimation consistency. Fig.4B shows the resulting partner control gain estimation as a function of the input control gain. These values are reported as the mean value over the final 8 seconds of the interaction.

It can be seen that the robot always estimates a value near to the partner's true control gain, however, a small error likely resulting from residual non-linear dynamics is present in all cases. This estimation error is worst at $L_{h,h} = 0$ in which the persistently exciting noise injected in the robot's desired trajectory would have no effect on the system. From the figure it can also be observed that the estimation is relatively consistent across trials with the maximum standard deviation given by 0.082 at $L_{h,h} = 2$ and the deviation less than 7.5% of the mean in all cases. This small deviation likely comes from the probabilistic nature of both the noise and UKFs.

To illustrate the convergence behaviour of the implemented UKF, Fig.4D shows the robot's partner gain estimation as a function of time for the 1st trial with $L_h = [0, 2, 0] \text{ N m rad}^{-1}$. It can be seen from this representative example that the estimated gains converge towards an oscillatory behaviour about the true value, taking about 6-8s to get to the vicinity of that value. This oscillation is produced as a result of the exciting noise input into the system and the friction compensation taking place in the robot. Compared to the simulation, these factors have a larger role because of the unmodelled dynamics for which the friction compensation is not completely cancelling.

B. Estimation of the 'virtual' human's desired trajectory

With the estimated VH control gain, it is possible to estimate the VH's new desired trajectory. For this purpose, analogously to Section IV-A we assume that the VH and robot's desired trajectories become the same trajectory as given by eq.(21). Fig.4E illustrates the results of the estimation of the partner's desired trajectory. The robot is able to estimate the correct magnitude and shape for the VH partner's desired trajectory. However, the estimation possesses a certain amount of error consistent with that observed in the estimated controller gains, likely due to the exciting noise input into the system and the friction compensation taking place in the robot.

C. Goal integration

Using the measurement given by eq.(19), the robot is able to exploit its estimation of the VH partner's desired trajectory to improve the estimation of the 'true' reference trajectory. The experiment is conducted with the same reference trajectory as is given by eq.(21) and the other parameters remain the same as in the previous subsection.

Fig.4F illustrates the average root mean squared error of the robot's estimated error state with and without integrating the estimated partner's desired trajectory under a range of different injected robot measurement noise levels. When the robot's measurement noise level is relatively high, it is clear that the estimation performance is improved with the estimated VH's desired trajectory integrated. When the robot's measurement noise level is low, the estimation performance is similar with or without goal integration, as there is not much room to improve the robot's accurate measurement.

D. Pilot study with human subjects

A pilot study was conducted with two human subjects by performing the same procedure as with the VH in Sections V-A–V-C: the robot first estimated the human subjects' gains (estimated as $L_{h,h} = 0.70$ and 0.51 for subjects 1 and 2), then their desired trajectories, which were combined with its own motion planning. The human subjects were required to follow the moving reference displayed on the monitor. All the parameters remained the same as in the previous subsection.

The average root mean squared error of the robot's estimated error state with and without integrating the estimated subject's desired trajectory is shown in Fig.4F. The results demonstrate the same pattern as the VH partner: the robot's state estimation was improved with integration of the estimated partner's desired trajectory. The robot's estimation performance is similar with lower noise level when compared to the larger improvement occurring with larger noise level. This means that the proposed algorithm will not improve the task performance if the robot is equipped with accurate sensors.

Note that the robot's estimations of the human subjects' gains and desired trajectories are not focused upon as in contrast to the VH no benchmark is available to be compared with. Together with the simulation results and the experimental results with the VH partner, these experimental results correspond to the observations of human-human interaction in [3] and demonstrate that human-robot interaction can be used to improve not only the reference trajectory estimation, but also the reference tracking of collaborative robots.

VI. DISCUSSION

This paper developed a new algorithm that can explain *haptic communication* between humans, and be used to improve human-robot performance in tracking. When humans in physical contact have to track the same reference, their central nervous system estimates each other's desired trajectory, which they integrate with their own visual estimation to improve the reference trajectory's estimation [3]. To model this neural mechanism, it was necessary to identify the partner's control gains and their desired trajectory, which was achieved here

through an unscented Kalman filter (UKF). The partner's desired trajectory could then be combined with their own reference visual observation to plan motion accordingly. Simulation and experimental results showed how this augmented sensing strategy improves the reference estimation performance across a range of different interaction noise values.

The proposed technique considered the case where both a robot and a human operator track the same independently defined trajectory. The case of tracking either different trajectories and/or references that dynamically change in response to the human is deferred to further work. The human control modeling assumed constant gains, which has been verified in tasks such as target reaching [21] or tracking [3]. Since human impedance varies with posture, the use of constant gains limits the trajectory used in the training to keep a relatively similar posture in order for the identified constant gains to still be valid. Although simple, target reaching and tracking corresponds to many typical tasks such as pick-and-place and navigation. More complex tasks may require estimating time-varying human control gains. On the other hand, the observability of the human-robot system dynamics-observation pair is a necessary condition for estimating the partner's control and estimating their motion planning. This condition can be fulfilled if the human and robot exchange rich haptic information. In this paper, observability between the human and robot pair was achieved by splitting the identification and required introducing a persistently exciting noise into the desired trajectory. The human control gain was first estimated on a known trajectory, before this information could be used to infer and track any unknown trajectory. However, humans are able to instinctively perform similar estimation concurrently provided that their interaction is suitably rich. Future works will be geared towards understanding the conditions for simultaneous estimation of control gain and desired trajectory.

By exploiting the interaction with the user, the novel augmented sensing algorithm could be used to improve the performance of various contact robots. For instance, if a robot has to help a human transporting an object [22], it can infer the human's planned movement and so improve its assistance. In shared control of semi-autonomous vehicles [23], the vehicle controller (i.e. the robot) may improve its sensing and performance in path tracking by using sensory information from the driver. Different from existing works that focused on collaborative control [4], this is (in our knowledge) *the first concept and algorithm to use the partner's sensing for improving own sensing and performance*. The pilot experiment with human users confirmed how this could improve the robot's performance by using feedback from the human partner, as interacting humans do [2]. We note that this algorithm could also be used to optimise the sensing of several interacting robots, and we expect that the interaction benefits would increase with the number of robots as was observed in human collectives [24].

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